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ANALYSTS EARNINGS FORECASTS: AN ALTERNATIVE DATA SOURCE FOR FAILURE PREDICTION

by

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This study investigates four properties of earnings forecasts made by financial analysts to determine if systematic differences in these properties exists between failing and healthy firms. The four properties are: The level of forecasts, forecast error, forecast bias, and forecast dispersion. Measures reflecting the four properties are used in models to distinguish failing and healthy firms and predict future bankruptcy. Results indicate that measures developed from analysts forecasts of future earnings can be exploited to distinguish failing from healthy firms.

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ANALYSTS' EARNINGS FORECASTS:

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Abstract

The purpose of this study is to determine if various measures developed from financial analysts forecasts of earnings for firms can be exploited in predicting future bankruptcy. The analysis consists of two major parts.

In the first part, four properties of analysts forecasts are discussed and investigated: forecast level, forecast dispersion, forecast error, and forecast bias. Tests are conducted to determine if there are systematic differences in the four properties for failing firms as compared to healthy firms in years prior to the bankruptcy of the failing firms. Several statistically significant differences are apparent. Failing firms tend to be associated with lower forecasted earnings, higher dispersion in earnings forecasts across multiple forecasters, greater error in forecasts, and over-optimistic forecasts. Differences between failing and healthy firms in how the properties change, both within years and across years, are also apparent.

In the second part of the study, measures reflecting the four properties, and how they change over time, are used to discriminate failing from healthy firms. Both univariate and multivariate approaches are attempted. Single measures and combinations of measures are able to out-predict a naive model, which classifies all firms as healthy, in distinguishing between groups. The single individual measure that best predicts future bankruptcy is mean forecasted earnings. Knowledge of mean forecasted earnings permits

correct classification of between 33% to 49% of firms that are incorrectly classified by the naive rule (depending on the year prior to bankruptcy). Combining various measures in a multivariate approach permits improved classification accuracy in particular situations. The general conclusion is that measures developed from forecasts of earnings do reflect conditions that are associated with future failure.

ANALYSTS' EARNINGS FORECASTS:
AN ALTERNATIVE DATA SOURCE FOR FAILURE PREDICTION

1.1 Introduction

Corporate bankruptcy, failure or distress can result in considerable costs to management, investors, creditors and customers. The prediction of corporate failure ex ante can provide the time to react and minimize those costs. The most common source of information for assessing financial health and developing models to predict failure is corporate accounting reports. Several past studies have assessed the ability of combinations of accounting ratios to predict bankruptcy. (See Zavgren [1983] for a review.)

There are, however, several weakness in the use of accounting data to predict corporate failure. Accounting data is produced only periodically, is historical rather than prospective, and reflects events that are primarily endogenous to the firm. Accounting measures are sensitive to the choice of accounting procedures, subject to "window dressing", and inevitable vary in magnitude across firms and industries as a function of the nature of operations and technology. In addition, because of interrelationships between measures, researchers have found that individual ratios are inconsistent predictors across tests and samples.

This study investigates the usefulness of another approach to the prediction of corporate failure, one involving the use of non-accounting information, specifically financial analysts forecasts (FAF) of a firm's future earnings. The purpose is to see if measures developed from analysts forecasts of earnings can be exploited to predict bankruptcy.

1.2 Background

Earnings are considered by investors and analysts to be a preferred expectational data item (Change and Most [1980]) and have the greatest information content of various accounting variables (Gonedes [1974]); thus there tends to be special importance attached to the information reflected in earnings. Various studies of financial analysts forecasts of earnings have been conducted (See Givoly and Lakonishok [1984] for review). Several qualities of FAF suggest their usefulness as an information source and their potential ability to aid in failure prediction. FAF tend to outperform mechanical models based on past historical earnings in predicting future earnings (Barefield and Comiskey [1975]; Collins and Hopwood [1980]; Fried and Givoly [1982]). This superiority is more pronounced in years where there is a turning point in the earnings trend (Barefield and Comiskey). FAF apparently contain information not captured by historical trends in earnings (Fried and Givoly) and may reflect inside information (Abdel-khalik and Ajinkya [1982]). Analysts revise their forecasts in response to information contained in quarterly earnings announcements (Brown and Rozeff [1979]) but the trend of FAF is smoother than actual trends (Crichfield, Dyckman and Lakonishok [1978]), suggesting that analysts separate a permanent from a temporary component in reported earnings numbers. Studies have indicated an association of FAF and revisions in FAF with stock prices (Neiderhoffer and Regan [1972], Givoly and Lakonishok [1979,1980], Elton, Gruber and

Gultekin [1981], Brown, Foster and Noreen [1985]). Securities trading strategies using FAF and revisions in FAF indicate that FAF have information content for the securities market (Givoly and Lakonishok [1980], Abdel-khalik and Ajinkya). Furthermore, FAF appear to be a more adequate surrogate for the securities market earnings expectations than are naive predictions based on historical earnings (Malkiel [1970], Malkiel and Cragg [1970], Fried and Givoly [1982]). Collectively these findings indicate that FAF are a useful, comprehensive piece of information which reflect information exogenous to firms' accounting systems.

Of particular interest in the context of bankruptcy prediction are measures of risk derived from FAF. The error in earnings forecasts has been shown analytically to be an appropriate indicator of uncertainty (Cukierman and Givoly [1982]). The dispersion of forecasts across analysts and the unpredictability of earnings have been shown empirically to be associated with traditional risk measures such as beta and the standard deviation of returns (Givoly and Lakonishok [1983]). In addition the dispersion of FAF has been shown to be superior to measures of beta, economy risk, information risk, and interest rate risk in explaining expected return (Malkiel [1981]). In short, dispersion and unpredictability in FAF may serve as useful proxies for risk. Such measures may be of "unique value to empirical researchers" because unlike most traditional risk measures, these are "ex ante" measures of risk (Givoly and Lakonishok [1984]).

In short, past attempts to predict corporate failure have in general relied on accounting data, which is historical, reflective of information primarily endogenous to the firm, subject confounding influences such as manipulation and the choice of accounting procedures, and provided only periodically. Financial analysts forecasts are prospective, reflective of a broad information set, and provided and revised in a timely manner. FAF can be expected to reflect macro-economic events, industry expectations and firm-specific non-accounting information (e.g. contracts, order backlogs, capital expenditures). Research has indicated that FAF and risk measures developed from FAF have useful information content.

1.3 Objective

The objective of this study is to empirically investigate the potential usefulness of measures developed from financial analysts forecasts of earnings in predicting corporate bankruptcy. In general the approach used is to identify a sample of failed firms and a matched sample of non-failed firms(Section 2), to create measures of various properties of analysts earnings forecasts and to investigate if the measures differ systematically between failing and healthy firms (Section 3), and to test the ability of the measures to discriminate between the two groups of firms (Section 4).

2. Data and Sample

2.1 The Data Source - IBES

The data source for analyst earnings forecasts was the

Institutional Brokers Estimate System (IBES) published by Lynch, Jones, and Ryan, a New York based brokerage firm. (An historical summary data tape covering each month from January 1976 through July 1985 was made available by Lynch, Jones, and Ryan.) Earnings forecast data for 4305 firms were available on the IBES tape. However, the period covered on the tape for individual firms ranged from one month to the maximum possible nine years, six months.

IBES contains summary statistics related to annual earnings-per-share forecasts up to two years prior to the announcement of the actual earnings number from multiple forecasters who report their predictions to the IBES service. Each month IBES provides information on the mean estimate, median estimate, high estimate, low estimate, standard deviation of estimates, number of upward revisions since the previous month, number of downward revisions, as well as various other data such as monthly stock price and adjustment factors related to stock splits.

2.2 Sample

F&S Index of Corporate Changes and the Wall Street Journal Index were reviewed for the period January 1977 through September 1985 to develop a list of firms declaring bankruptcy. The list was cross-referenced with firms on the IBES data tape. IBES contained data for 98 bankrupt firms, but 30 firms were dropped because the period of data coverage on IBES was following bankruptcy or because the number of months of data coverage was too short. The sample consisted of 68 bankrupt firms.

Using rankings provided in the annual Wards Directory of

Leading U.S. Corporations, each bankrupt firm was matched with a non-bankrupt firm from the same industry (three digit SIC codes) and of approximately the same size.

Matching on industry is desirable to control for industry characteristics and conditions. Forecast uncertainty may be related to industry. Furthermore, information events may have industry-wide implications leading to industry-wide revisions in earnings forecasts.

Matching on size is desirable because size is associated with risk, probability of bankruptcy, analyst attention, and most likely, the number of sources from which consensus forecasts and summary statistics on the IBES tape are developed. Using total assets as a measure of size, 58% (42%) of bankrupt firms were larger (smaller) than their non-bankrupt matched firm. Using total sales as a measure, 50% of bankrupt firms were larger than their non-bankrupt match. Both parametric (t-test) and non-parametric (wilcoxon sign rank) tests revealed no significant difference in mean size between bankrupt and non-bankrupt groups, so the matching process was apparently successful.

The 68 matched pairs represent the maximum sample available for the analysis conducted. However, data for each firm was not available on IBES for each month and year of the test period. In addition, in some months where data was available, IBES included forecasts from only one analyst while certain measures used in the analysis (e.g. standard deviation of multiple forecasts) required forecasts from more than one source. Consequently, many individual tests were conducted on sample sizes less than 68.

Matching on fiscal year-end would perhaps be desirable but was not possible without a great reduction in sample size. Data for each firm in a given matched pair were however taken from the same fiscal year. Within a given year there is substantial evidence that the properties of analysts forecasts change as the year-end approaches. For example forecasts tend to become more accurate as the end of a reporting year approaches. However, data in the study is analyzed in "event" time rather than "calendar" time, which minimizes any problem associated with firms having different fiscal year ends.

2.3 A Word on Notation

Notation used in the study also refers to event time. Two events are of importance: the year in which bankruptcy is declared for the bankrupt firm and the month relative to fiscal year-end within any year. The notation used treats bankruptcy as time "zero" and counts backward in time such that both years and months increase as the time before bankruptcy or year-end increases. Year zero is the year in which bankruptcy is declared for a bankrupt firms (and the corresponding fiscal year for the corresponding healthy firm in a matched pair). Year one is the fiscal year immediately prior to the year in which bankruptcy is declared. Within any given fiscal year, month zero is the last month in the year (e.g. December for a firm with December 31 year-end). Month three is three months prior to year-end (e.g. September), and so on. Tests are presented for two years prior to bankruptcy at three month intervals corresponding to the end of quarters.

3. Properties of Analysts Earnings Forecasts

3.1 Measurement of Properties

Four properties of analysts earnings forecasts were investigated: 1. The average (mean) forecasted earnings provided by forecasters (available on IBES); 2. The accuracy in forecasts when compared to actual earnings; 3. The bias in forecasts(whether they under or over predict actual earnings); and 4. The dispersion in forecasts across multiple forecasters.

First, measures to reflect the four primary properties of interest were constructed as follows:

Mean Forecast = ME = $\hat{Y}_{tm}$

Forecast Error = ERR = $\left|\hat{Y}_{tm} - Y_t\right|$

Forecast Bias = BIAS = $\hat{Y}_{tm} - Y_t$

Forecast Dispersion = SD = Standard deviation of forecasts for year t at month m across multiple forecasters.

Where:

$\hat{Y}_{tm}$ = Mean Forecasted EPS for year t provided at month m.

Y_t = Actual reported EPS for year t

t = 1 or 2 (years prior to bankruptcy)

m = 0,3,6,9 (months prior to year end)

(Each of these measures is undeflated. Alternative measures were created by deflating by stockprice and, where appropriate, by reported earnings. Overall findings were the same and no results using deflated measures are reported.)

Second, to reflect how the properties change <u>within</u> a given forecast year (intra-year changes), the difference between measures of the properties taken at two points within a year was computed. For example, the change in mean forecasted earnings (MECHG) between the forecast at year end and at months earlier in the year was determined as follows:

$$MECHG = ME_{t,o} - ME_{tm} \qquad \text{Where } m=3,6 \text{ or } 9$$

Analogous measures reflecting the intra-year change in forecast error (ERRCHG) and in forecast dispersion (SDCHG) were developed. (The intra-year change in forecast bias is mathematically equivalent to MECHG and thus is not considered.)

Third, to reflect how properties change <u>across</u> different years (inter-year trends), the difference between measures of the properties taken (at the same month) in successive years was computed. For example the trend in mean forecasted earnings (METRND) was determined as follows:

$$METRND = ME_{tm} - ME_{t-1,m} \qquad \text{Where } t = 1 \text{ or } 2$$

Analogous measures reflecting inter-year trends in forecast error (ERRTRND) , forecast bias (BTRND) and forecast dispersion (SDTRND) were developed.

<u>3.2 Questions of Interest</u>

In general three questions are addressed: Are there systematic differences in the four properties of interest between failing and healthy firms? Are there systematic group differences in how the properties change within a forecast year? Are there systematic group differences in how the properties change across forecast years? Group means for each of the measures of interest and non-parametric wilcoxon tests of significance of the difference in group means are presented in following tables.

3.3 Mean Forecasted Earnings

One obvious place to look for differences between failing and healthy firms is simply in the level of future earnings predicted for firms in each group. Although low earnings does not imply bankruptcy and high earnings does not insure health, one would expect some relationship between the level of earnings and the probability of future failure. While reported earnings may contain information relevant to distinguishing between groups, forecasted earnings are future looking and consequently have the potential of reflecting aspects of firm health that have not yet been reflected in reported earnings.

Table 1 shows highly significant test results related to the level of forecasted earnings. Several findings of note: First, looking at ME, for all months within a forecast year, for both years prior to bankruptcy, significantly lower earnings are predicted for the failing firms.

Second, looking at MECHG, negative values indicate a decline in the level of forecasted earnings as year-end approaches. There are negative MECHG values for both the failing and healthy firms.

TABLE 1

MEAN LEVEL OF FORECASTED EARNINGS

VARIABLE	YEAR	MONTH	GROUP MEANS FAILING	HEALTHY	WILCOXON Z	α
ME	1	0	-.86	1.57	-6.17	.000
		3	-.27	1.77	-6.15	.000
		6	.44	1.95	-4.91	.000
		9	.88	2.02	-4.23	.000
	2	0	-.81	1.69	-4.94	.000
		3	.07	1.87	-4.25	.000
		6	.58	2.10	-3.36	.001
		9	1.24	2.14	-2.99	.003
METRND	1/2	0	-.08	-.03	-3.85	.000
		3	-.07	-.01	-2.51	.012
		6	-.11	.01	-1.42	.155
		9	-.42	.03	-1.78	.075
	2/3	0	-1.46	-.09	-3.07	.002
		3	-1.10	.04	-2.80	.005
		6	-.85	.05	-2.68	.007
		9	-.57	.09	-2.39	.017
MECHG	1	0/3	-.72	-.19	-2.99	.003
		0/6	-1.34	-.29	-3.75	.000
		0/9	-1.89	-.38	-4.54	.000
	2	0/3	-.89	-.17	-3.71	.000
		0/6	-1.51	-.27	-3.66	.000
		0/9	-2.28	-.35	-3.46	.001

This is not surprising. Forecasts in general could be optimistic and require downward revisions if general economic conditions were deteriorating. The fact that the measures are taken in years just prior to bankruptcy for the failing firms, coupled with the fact that bankruptcies increase in times of overall economic stagnation, is consistent with those years being periods of optimistic forecasts even for the healthy firms. Despite the declining earnings forecasts for both groups, the MECHG tests indicate significantly greater intra-year declines for failing firms.

Third, looking at METRND, it is also apparent that the failing firms exhibit a downward trend in earnings forecasts across years, which is not exhibited by the healthy firms. The tests suggest that measures reflecting forecasted earnings, and changes in forecasted earnings both within and across years may be potentially useful in distinguishing failing from healthy firms.

3.4 Accuracy - Forecast Error

Past investigations of the accuracy of analysts forecasts (see Givoly and Lakonishok [1984] for a review) have generally focused on two questions: Are analysts forecasts more accurate than forecasts from mechanical models? And how do analyst's forecasts compare to management forecasts? Results of studies comparing analysts forecasts with forecasts from numerous types of mechanical models have occasionally been contradictory, but in general analyst forecasts appear to out-perform mechanical models. Results of studies comparing analyst forecasts to management forecasts suggest a slight but insignificant advantage to management. These results are not surprising. One would expect analysts to out-perform mechanical models given the wider information set on which analysts may rely. Likewise, one would not be surprised by the essentially similar performance between analysts and management given their similar information sets and the incentives for management to provide information to analysts (Ajinkya and Gift [1984]). The objective here is to test for systematic differences in analyst accuracy between failing and healthy firms.

Table 2 provides test results. Forecast errors (ERR) are consistently significantly greater for failing firms in both years prior to bankruptcy, regardless of the month in which the forecast is made. This is consistent with the argument of Cukierman and Givoly [1982] that forecast errors reflect risk. Past research has indicated that forecast errors tend to decline (i.e. increasing accuracy) as year-end approaches (e.g. Elton, Gruber and Gultekin [1984]). Increasing accuracy is evident in the present sample for both failing and healthy firms (reflected in negative ERRCHG measures). This is expected since more and better information becomes available as the period progresses. Forecast errors, however, are associated with risk and uncertainty. For the failing firm group, the passage of time also implies the approach of bankruptcy. One might hypothesize that approaching bankruptcy will result in a relatively smaller increase in forecast accuracy (less decrease in forecast error) for failing firms. On the other hand, forecasts for failing firms are less accurate overall. Thus there

TABLE 2

FORECAST ERROR

VARIABLE	YEAR	MONTH	GROUP MEANS FAILING	HEALTHY	WILCOXON Z	α
ERR	1	0	4.17	.40	5.97	.000
		3	5.16	.55	5.46	.000
		6	6.63	.72	5.95	.000
		9	6.66	.89	6.01	.000
	2	0	1.40	.43	3.27	.001
		3	2.07	.58	3.86	.000
		6	2.10	.63	3.51	.001
		9	2.97	.75	3.00	.003
ERRTRND	1/2	0	3.65	.05	2.92	.004
		3	4.11	.08	1.68	.093
		6	5.00	.21	1.74	.082
		9	4.22	.30	1.85	.064
	2/3	0	.07	.14	1.23	.218
		3	.11	.21	-.48	.632
		6	.06	.05	-.03	.977
		9	.83	.05	1.02	.309
ERRCHG	1	0/3	-.87	-.15	-.79	.427
		0/6	-1.81	-.33	-2.94	.003
		0/9	-2.01	-.50	-3.37	.001
	2	0/3	-.64	-.15	-3.11	.001
		0/6	-1.01	-.19	-2.48	.013
		0/9	-1.86	-.30	-2.54	.011

is more "room for improvement" as new information arrives throughout the year. The larger forecast errors for failing firms may allow for greater improvement and thus greater decrease in forecast errors. These two arguments suggest competing reasons for systematic group differences in intra-year changes in forecast accuracy. The later reason apparently holds in the sample. MECHG measures are significantly <u>more</u> negative for failing firms, indicating greater improvement in accuracy. ERRTRND measures on the other hand are larger for failing firms (in year 1) indicating increasing error and less accuracy across years. This is consistent with increasing risk as bankruptcy approaches being reflected in increasing forecast error.

3.5 Forecast Bias

If forecasts are rational (Muth [1961]) they should be unbiased. While forecasters cannot be expected to predict without error, rational forecasters should in general be able to predict without systematic error. Consistent systematic error would be inconsistent with rationality since rational forecasters should use the information in past forecast errors to improve future forecasts. Unbiased forecasts imply that

$$\text{Actual} = \text{Forecast} + e$$

where e is a random error with zero expectation.

Studies by Critchfield, Dyckman and Lakonishok [1978], Givoly [1985], and Malkiel and Cragg [1980] have examined analysts forecasts for bias and have failed to reject the hypothesis that forecasts are unbiased. (However, Givoly and Lakonishok [1984],

TABLE 3

FORECAST BIAS

VARIABLE	YEAR	MONTH	GROUP MEANS FAILING	HEALTHY	WILCOXON Z	α
BIAS	1	0	3.93	.00	4.69	.000
		3	5.09	.18	5.53	.000
		6	6.63	.27	6.22	.000
		9	6.66	.36	6.29	.000
	2	0	1.03	.17	2.97	.003
		3	1.86	.33	4.06	.000
		6	2.05	.43	3.92	.000
		9	2.87	.50	3.18	.002
BTRND	1/2	0	3.99	-.07	1.89	.058
		3	4.37	-.07	1.46	.145
		6	5.08	-.07	2.14	.032
		9	4.36	-.04	2.37	.018
	2/3	0	-.17	.07	-.44	.661
		3	.10	.22	.55	.584
		6	.18	.25	-.10	.921
		9	.90	.24	.26	.792

citing Barefield and Comiskey [1975] and Fried and Givoly [1982], conclude that there is an "accumulation of evidence," though statistically insignificant, that an upward bias may be present in analysts forecasts.)

The finding of no systematic bias is consistent with rational forecasts and with the proper processing and utilization of information available in the past realizations of earnings and forecast errors. The immediate concern here is whether there is a difference in the bias of forecasts between healthy and failing firms.

Results for bias tests are in table 3. Note that group means for BIAS for both the failing and healthy firms are consistently positive, consistent with the tendency toward an upward bias (overestimation) cited by Givoly and Lakonishok. T-tests (not reported) indicate that the bias is significantly different from zero for the failing firms but not the healthy firms. More importantly the bias for failing firms is significantly greater for the failing firms, regardless of the month within the forecast year. Measures of the trend in bias (BTRND) from year 2 to year 1 are significantly higher for failing firms, indicating increasing overestimation of earnings as bankruptcy approaches.

3.6 Forecast Dispersion

Previous research has investigated the dispersion across analysts forecasts as a measure or indication of uncertainty. Cukierman and Givoly [1982] present a model in which the dispersion of forecasts across forecasters is positively associated with the

TABLE 4

FORECAST DISPERSION

VARIABLE	YEAR	MONTH	GROUP MEANS FAILING	HEALTHY	WILCOXON Z	α
SD	1	0	.66	.22	3.10	.002
		3	.49	.23	2.94	.003
		6	.44	.25	3.38	.001
		9	.44	.24	2.29	.022
	2	0	.66	.19	2.01	.044
		3	.43	.25	2.50	.013
		6	.29	.25	1.69	.092
		9	.31	.29	1.18	.238
SDTRND	1/2	0	.29	.05	1.92	.054
		3	.17	-.02	2.67	.008
		6	.21	.02	4.08	.000
		9	.16	-.04	2.45	.015
	2/3	0	.50	.05	.32	.752
		3	.18	.07	1.20	.231
		6	.05	.02	.56	.578
		9	.12	.11	1.33	.183
SDCHG	1	0/3	.09	.00	-.44	.662
		0/6	.22	-.03	.31	.757
		0/9	.28	-.00	.82	.414
	2	0/3	.25	-.05	.34	.731
		0/6	.42	-.04	1.78	.074
		0/9	.49	-.10	1.81	.069

dispersion of the distribution of expected earnings and therefore with the cross-sectional error in forecasts. Empirical evidence supported their model; measures of dispersion were positively associated with measures of forecast error. Results from Elton, Gruber and Gultekin [1984] also document this relationship. Cukierman and Givoly argue that the cross-sectional error in earnings is the empirical counterpart of uncertainty. Dispersion of earnings forecasts have also been found to be associated with traditional risk measures such as beta, the standard deviation of returns and earnings growth variability (Givoly and Lakonishok [1983].) The purpose here is to determine if measures of dispersion differ systematically between failing and healthy firms as bankruptcy approaches. The implicit assumption is that forecast dispersion measures may reflect risk that is ultimately manifested in bankruptcy.

Given that dispersion may reflect uncertainty, one would hypothesize greater dispersion for failing firms and increasing dispersion, both within and across years, for failing firms. (Tests using alternative measures, such as the range, variance and coefficient of variation, were conducted with similar results.)

Tests for group differences in SD, reported in table 4, show significantly greater dispersion for failing firms throughout the two years prior to bankruptcy (year 2, month 9 excepted). Observing the group means for SD within each year, there is a general tendency for dispersion to increase for failing firms and decrease for healthy firms as the year end approaches. This is consistent with increasing uncertainty for failing firms as bankruptcy approaches (although the SDCHG tests indicate that this group difference is not generally significant). Tests on SDTRND indicate significantly greater increase in dispersion for failing firms from year 2 to year 1. Again this is consistent with impending failure increasing uncertainty and being reflected in greater dispersion of forecasts.

4. Tests of Discrimination

4.1 Measures used

The previous results indicate that there are group differences for each of the four primary properties of earnings forecasts in years prior to bankruptcy, and group differences in how those properties change both within years and across years. The question here is whether measures of those properties and their changes can be exploited to predict future bankruptcy. For each year (1 and 2) prior to bankruptcy, a single measure was selected to represent each of the primary properties (ME, ERR, BIAS, SD), each of the intra-year changes (MECHG, ERRCHG, SDCHG) and each of the inter-year trends (METRND, ERRTRND, BTRND, SDTRND); eleven variables in total. Measures of the primary properties are taken at year end (month 0); measures of inter-year trends used month 0 measures in successive years; measures of intra-year changes used the difference between month 0 and month 6 measures. The selection, emphasizing year end measures, is somewhat arbitrary but increases sample size because more forecasts become available as the year-end approaches. Since measures taken at different months within a year tend to be highly correlated for a given firm, use of measures developed at months different from those selected could be expected to lead to similar findings.

4.2 Univariate Analysis: Classification, Verification and Prediction

As a first step toward using forecast information to predict failure, a univariate analysis was conducted. The approach used follows Beaver (1966). The procedure is straight forward. Sample firms were rank-ordered independently on each of the measures of interest. The rank-ordered values for a given measure were visually observed. A cutoff or threshold value of the measure was selected to divide sample observations into failing and healthy firms. Cutoff values were selected that minimized the percentage of firms misclassified. Results using measures from year 1 and year 2 are provided in the top part of tables 5 and 6, respectively.

Five items relating to errors in classification are provided under the "classification" column in the tables: The type 1 error is the percentage of failing firms misclassified as healthy. The type 2 error is the percentage of healthy firms misclassified as failing. The average error is a weighted average of the type 1 and type 2 errors and thus represents the overall classification error rate. The percentage in the Naive column is provided as a benchmark for comparison. It represents the frequency of misclassification errors from the following naive classification misclassification errors from the following naive classification rule: assign all firms to the group (failing or healthy) with the highest frequency in the sample. (This generally meant classifying all firms as healthy because data limitations were such that healthy firms outnumbered failing firms in the samples used to develop the cutoffs).

The final item in the table is a rough measure of the efficiency (EFF) of using the cutoff on a variable to classify firms when compared to using the naive approach. It is calculated as the error rate from the naive approach minus the error rate from the cutoff approach divided by the error rate from the naive approach, and thus measures the percentage of firms that were misclassified by the naive approach that were correctly classified by the cutoff approach. EFF equals zero when the naive and cutoff approach have the same overall error rate. Higher positive values of EFF indicate increasing superiority of the cutoff approach over the naive rule, with a value of one indicating no errors in classification. Negative values indicate that the cutoff approach was less successful than the naive rule.

Classification results, however, typically overstate the value of an approach in discriminating between two groups since the classification rule (cutoff value) is applied to the same sample on which it is developed. Validation is required. Ideally validity should be assessed on a sample unrelated to that used to develop the classification rule, a hold out sample. Operationally this can be achieved by randomly dividing the sample into two subsamples,

TABLE 5
DISCRIMINATION– YEAR 1 MEASURES

VARIABLE	CUTOFF	CLASSIFICATION YEAR 1 DATA					VERIFICATION ON YEAR 1 DATA					PREDICTION ON YEAR 2 DATA				
		ERROR RATE %					ERROR RATE %					ERROR RATE %				
		Type1	Type2	Ave	Naive	Eff	Type1	Type2	Ave	Naive	Eff	Type1	Type2	Ave	Naive	Eff
ERR	> .565	8	17	14	31	.55	31	15	20	31	.29	61	15	32	38	.16
ERRTRND	> 2.88	56	0	14	26	.46	61	0	16	26	.38	92	2	35	36	.03
ERRCHG	<- .83	35	14	20	26	.23	60	9	22	26	.15	58	7	23	36	.36
BIAS	<-1.57	46	0	16	31	.48	35	8	16	31	.48	78	5	32	38	.16
BTRND	<-2.46	50	0	13	26	.50	61	0	16	26	.38	85	7	35	36	.03
SD	> 1.09	74	2	25	33	.24	74	13	33	33	.00	89	2	36	40	.10
SDTRND	> .31	63	6	26	35	.26	48	12	25	35	.29	69	7	31	38	.18
SDCHG	> .175	60	10	27	33	.18	76	10	32	33	.03	74	11	35	39	.10
ME	< .11	37	10	22	43	.49	37	10	22	43	.49	62	5	30	45	.33
METRND	< -.46	52	17	31	39	.21	68	14	35	39	.10	60	18	36	42	.14
MECHG	<-1.17	56	8	27	40	.33	70	8	33	40	.18	60	10	32	43	.21
<u>INDEXES</u>																
ALL	> 2	0	6	4	25	.83	17	3	6	25	.75	69	16	33	33	.00
PR	> 1	28	4	10	23	.57	43	10	18	23	.21	62	8	26	34	.23
PRTRND	> 1	0	8	6	25	.75	8	11	10	25	.58	63	16	31	33	.06
PRCHG	> 1	0	14	11	24	.54	46	7	16	24	.31	52	13	26	34	.22

TABLE 6

DISCRIMINATION– YEAR 2 MEASURES

VARIABLE	CUTOFF	CLASSIFICATION ON YEAR 2 DATA					VERIFICATION ON YEAR 2 DATA					PREDICTION ON YEAR 1 DATA				
		ERROR RATE %					ERROR RATE %					ERROR RATE %				
		Type1	Type2	Ave	Naive	Eff	Type1	Type2	Ave	Naive	Eff	Type1	Type2	Ave	Naive	Eff
ERR	> .70	64	8	29	38	.24	56	17	31	38	.18	19	15	16	31	.48
ERRTRND	> 1.26	81	7	32	36	.11	88	9	38	36	-.06	44	14	22	26	.15
ERRCHG	< -.63	42	9	21	36	.42	42	9	21	36	.42	35	23	26	26	.00
BIAS	< -.305	44	15	26	38	.32	56	17	31	38	.18	19	19	19	31	.39
BTRND	<-1.43	73	11	33	36	.08	85	9	36	36	.00	44	10	19	26	.27
SD	> .70	72	4	31	40	.23	72	4	31	40	.23	67	9	28	33	.18
SDTRND	> .28	50	7	31	38	.18	96	5	40	38	-.05	63	6	26	35	.26
SDCHG	> .40	71	2	29	39	.26	68	6	30	39	.23	80	6	31	33	.06
ME	< .39	48	6	25	45	.44	50	8	27	45	.40	33	16	24	43	.44
METRND	< -.13	40	22	30	42	.29	49	24	36	42	.14	37	32	34	39	.13
MECHG	< -.61	42	14	26	43	.40	40	19	28	43	.35	38	25	30	40	.25
<u>INDEXES</u>																
ALL	> 3	44	13	23	33	.31	75	3	27	33	.19	8	14	13	25	.50
PR	> 2	62	4	23	34	.31	54	8	23	34	.31	50	6	16	23	.29
PRTRND	> 2	56	13	27	33	.19	50	19	29	33	.13	8	14	13	25	.50
PRCHG	> 2	43	7	19	34	.43	61	4	24	34	.30	23	14	16	24	.31

developing the cutoff value on each subsample, and using the cutoff from each subsample to classify the firms in the other subsample. Findings from using this approach are unbiased. They are contained in the second set of results under the "verification" column.

Another approach to validation is to determine validity across time. The remaining column in the tables, labeled "prediction", shows the results of applying the cutoffs developed in one year prior to bankruptcy to the measures available for sample firms in another year.

Several broad conclusions can be drawn from the tables.

a. The frequency of type 1 errors is consistently greater than the frequency of type 2 errors. This is unfortunate since the costs associated with type 1 errors are likely to be greater than those associated with type 2 errors. But given the approach used, such results are likely to occur if, as in reality, the frequency of healthy firms in a sample is greater than the frequency of failing firms.

b. EFF values are generally positive, indicating that this univariate approach does have some ability to identify group membership. However, the superiority of using cutoff values as compared to the naive approach is frequently marginal for some of the measures.

c. Regardless of which year the cutoffs are developed on, there is a tendency for errors to be smaller in year 1 than year 2. This is not surprising since, if the measures have any ability to identify failing firms, the properties of failing firms should be more evident as bankruptcy approaches.

d. One would like to have a measure (or measures) that a) is valid in that it performs well on the verification tests and b) is consistent, in that it performs well in more than one year prior to bankruptcy, i.e., performs well in the prediction tests. Overall, measure ME performs best. Average error rates for ME tend to be low and efficiency rates relatively high. The ability of a cutoff based on ME to outperform the naive approach tends to be the most consistent across the verification and prediction tests and across the years. Regardless of the year (1 or 2) in which the cutoff value is determined, use of ME allows for a discrimination of firms in the two years prior to bankruptcy which is markedly better than a naive rule. Efficiency indicators suggest that about 33-49% of firms misclassified by the naive rule can be correctly classified using a cutoff based on ME.

4.3 Multivariate Index Approach

By far the most popular approach to developing failure prediction models has been multiple discriminant analysis. (See Zavgren [1983] for review.) However, its use in bankruptcy studies has been criticized (e.g. Moyer [1977]). Moses and Liao [1986] explain procedures for the construction of a "failure index" that in their study out-performs discriminant models in predicting failure. Procedures analogous to Moses and Liao are used here to create indexes using several of the individual measures. (Discriminant models were constructed, but were not superior to the index approach reported here). The basic procedures for creating an index are simple. For each of the individual measures used in the univariate tests, firms were assigned a score of 1 if they fell on the "bankruptcy" side of the cutoff, and 0 otherwise. Then scores were totaled for variables that were to be included in a given index. Four different indexes were examined as follows (each included scores from the variables indicated):

1. Primary Variables (PR): ME, ERR, BIAS, SD
2. Primary & Trend Variables (PRTRND): ME.ERR,BIAS,SD: METRND, ERRTRND, BTRND, SDTRND
3. Primary & Change Varialbes (PRCHG): ME, ERR, BIAS. SD: MECHG, ERRCHG, SDCHG
4. All Variables (ALL): all eleven measures

Firms were rank ordered on the total score provided by the given index and a cutoff score that minimized errors in classification was determined by viewing the ranking. Classification results for the four indexes are provided in the bottom part of tables 5 and 6. As with the univariate aporoach, the procedure was applied to holdout samples in the same year and to data from a different year. The analogous results are reported under the verification and prediction columns in tables 5 and 6. (The verification procedure on holdout sample is unbiased because the holdout sample is used neither in selecting the variables to be included in the index nor in determining the cutoffs.)

Focusing primarily on the efficiency (EFF) statistics as a summary of how well the indexes perform, some general findings can be noted:

a. As with the univariate measures, accuracy tends to be higher in year 1 than year 2 regardless of the year on which the cutoffs are developed. Again, this is not surprising as the characteristics associated with failure should be more evident closer to failure.

b. Looking at the verification and prediction columns, the PRTRND index out-performs the PRCHG index when applied to year one data while the PRCHG index out-performs the PRTRND index when applied to year two data. This holds regardless of whether the indexes are developed on year one or year two data, and was also true in the univariate tests.

c. The ALL index appears to be the best of the indexes when applied to year one data and one of the worst when applied to year two.

d. Each of the indexes is superior to the univariate measures in some tests, but for consistent performance (i.e. good validation both on the holdout sample and when applied to data from other years, and insensitivity to the year in which the cutoffs are developed) none of the indexes out-performs the univariate results using just ME.

5. Conclusions

Tests results indicated that measures of mean forecasted earnings, forecast error, forecast bias and forecast dispersion, as well as changes in those measures over time, do reflect conditions that are apparently associated with impending bankruptcy. All measures investigated in the study were able to outperform a naive classification rule. The most useful single measure for predicting future failure is mean forecasted earnings, but indexes combining multiple measures reflecting the properties of analysts earnings forecasts are superior to mean forecasted earnings in particular situations. The measures and indexes tested here are not in general superior to models using accounting data (see Zavgren [1983] for a summary), however, other approaches to measurement of variables or model construction could alter that conclusion.

There are several areas for future research. First alternative measures developed from earnings forecasts, measures developed at alternative months within a year, or measures developed from management earnings forecasts could be investigated. Second more sophisticated model building approaches such as logit could be explored to determine if results improve. Third, and perhaps the most fruitful area for research, models combining measures of earnings forecast properties with traditional financial accounting ratios could be explored. The fact that analysts earnings forecasts do reflect failure relevant information and, being forward looking, have the potential to reflect evolving events prior to the publication of financial statements, indicates that signals provided by analysts earnings forecasts could be used as an early warning of failure in conjunction with traditional reliance on financial accounting ratios.

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